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Research Article

Artificial Intelligence and Metaheuristic-Based Location-Based Advertising

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Location-based services (LBS) are necessary for obtaining the important details since the user needs vary based on the location. Location-based advertising (LBA) are utilized for abandoning the user location and to offer assistance by using the obtained information. Therefore, an efficient machine learning and metaheuristic-based model referred as GANM is designed for LBS. Initially, the potential location information is evaluated utilizing the geographic information system (GIS). Thereafter, significant features are computed using the location data. Obtained features are then segmented to improve the process of LBS. Adaptive network-based fuzzy inference system (ANFIS) is then utilized to efficiently classify the user data. Finally, the optimization of classified documents is achieved using the nondominated sorting genetic algorithm-III (NSGA-III). Extensive experiments are performed to validate GANM for LBS. Comparative analyses reveal that GANM outperforms the competitive LBS models in terms of F-score, accuracy, sensitivity, specificity, and area under curve by 2.2734%, 2.3981%, 2.3947%, 2.4271%, and 2.1638%, respectively.

1. Introduction

With the technological advancements, mobile advertisement is extensively utilized for short message service for interactive advertisements [1]. Location-based advertising (LBA) is one of the well-known mobile advertisement approach [2]. Different artificial enabled location-based services (LBS) are proposed for mobile advertising using various algorithms such as random forest (RF), support vector machine (SVM), and artificial neural networks (ANN) [3–5].

In [6], personal transitional location was predicted using modified SVM. It has shown better performance than the linear model and standard SVM. In [7], suitable places for live campaigns were predicted by considering LBS. Individual feature-based and SVM models were implemented. It was found that SVM achieved 30% more accuracy than the standard model. In [8], user attitudes related to smartphone ads were predicted by considering SVM. Similarity attraction and pattern recognition models were utilized for achieving the better performance. In [9], multifeatures were utilized to predict the friends using LBS-based social networks. SVM was used for friendship prediction.

In [10], J48 and apriori-based probability tree classifier (APTC) were used to predict the human movement sequence. The patterns were evaluated using social, temporal, and spatial data that help the model to achieve better accuracy. In [11], future locations were predicted using supervised learning to help LBS. Various classifiers were applied on various features that had achieved better performance. In [12], ensembling of J48, NB, and ANN was achieved for predicting the locations of mobile crowd. Hybrid features were utilized to achieve the performance

further. In [13], ANN was applied to gather realtime information for LBS. GPS was used to detect the mobile locations and then radius of given location was predicted.

It is found the development of efficient artificial intelligence-based LBS is still an open area of research. The used machine learning models such as SVM, RF, J48, and ANN suffer from the overfitting problem [14, 15]. Besides this, the predicted LBS further need to be optimized using optimization techniques [16, 17]. Therefore, in this study, an efficient machine learning and metaheuristic-based model is designed for LBS.

Additionally, location-based advertisement (LBS) can be defined as an optimization problem. As the main objective of LBS is to maximize the long-term average revenue. There are two main constraints on LBS problem, i.e., prevents user saturation and disengagement and long-term average budget to be spent for each organization. Thus, it can be resolved using multiobjective metaheuristic technique. Therefore, in this study, nondominated sorting genetic algorithm-III (NSGA-III) is selected. As it can handle multiobjective problems with better convergence speed, NSGA-III do not suffer from stuck-in local optima and premature convergence issues too. The key contributions of this study are outlined as follows:

(1) An efficient machine learning and metaheuristic-based model refereed as GANM is designed for LBS.
(2) The geographic information system (GIS)-based location features are computed using the location data.
(3) Obtained features are then segmented to improve the process of LBS. Adaptive network-based fuzzy inference system (ANFIS) is then utilized to efficiently classify the user data.
(4) Finally, the optimization of classified documents is achieved using NSGA-III.
(5) Extensive experiments are performed to validate GANM.

The remaining study is structured as follows. Literature review is presented in Section 2. Proposed methodology is demonstrated in Section 3. Section 4 presents the comparative analyses. Finally, Section 5 concludes the paper.

2. Related Work

This section presents the related work related to LBS.

Tan et al. [18] used partial least squares structural technique to analyze the social media advertisements. An integrated framework also implemented to understand the consumers preferences using interactive theory, personal factors, and mobile technology acceptance model. Li and Xu [19] proposed a diversity-aware mobile advertising framework (D-AdFeed) to provide diverse advertisements to the clients. This problem was formulated as multichoice knapsack problem. It was solved using greedy and genetic algorithms. Goh et al. [20] investigated the search behavior and responses to advertisements using Logit and Poisson count models. Li and Du [21] provided context-aware advertisements to both merchants and clients by implementing a targeted mobile advertising system.

Haider et al. [22] explored the fraudulent activities in the mobile advertising using the ensemble-based method. Ryu and Park [23] used the persuasion knowledge model to assess the knowledge of consumers regarding location-based advertising. Lu et al. [24] proposed the expectation confirmation model to analyze the repurchase behavior of the consumers. Shin and Lin [25] analyzed the relationship between consumers' perceptions and advertising avoidance. Hu et al. [26] proposed recommendation approach based on user similarity for mobile advertisement. Yang et al. [27] proposed an advertising model using the emotion-based and technology-based evaluations. Sharma et al. [28] used neural network and partial least structure to improve the purchase intention of the consumers in the mobile advertisement.

Moses [29] used network-based positioning for mobile advertising to deliver the SMS to consumers. Lee et al. [30] utilized plot placement animation to implement the location-based mobile advertising. Shoaibi and Rassan [31] presented mobile advertising model to provide the location-based services. Edirisinghe et al. [32] proposed a framework for advertising using web and mobile applications. This framework can be used by the developers and advertise in their applications.

Hu et al. [33] assessed the severity and impact of data collection through location-based advertisements using an automated fine-grained data collection approach. Evans et al. [34]proposed an intelligent mobile advertising system using global navigational satellite systems (GNSS) and location-based services. Arya et al. [35] utilized fuzzy and NB to implement the intelligent targeted advertising approach. This model can help to assess the individual customer needs.

It is observed that the used machine learning models such as SVM, RF, J48, and ANN suffer from the overfitting problem. Besides this, the predicted LBS further need to be optimized using optimization techniques. Therefore, an efficient integrated model is designed in the study to overcome the aforementioned problems.

3. Proposed Model

This section presents the mathematical background of the proposed location-based advertising using the ANFIS and NSGA-III model. Figure 1 shows GANM which presents the step-by-step flow of GANM. Initially, the potential location information is evaluated utilizing GIS. Thereafter, significant features are computed using the location data. Obtained features are then segmented to improve the process of LBS. ANFIS is then utilized to efficiently classify the user data. Finally, the optimization of classified documents is achieved using NSGA-III.

3.1. Adaptive Neuro-Fuzzy Inference System. ANFIS is improved version of artificial neuro-networks (ANN). Fuzzy membership functions are used to convert the features to multivalent values. Remaining layers trained the model similar to ANN. Figure 2 shows the architecture of the ANFIS model.

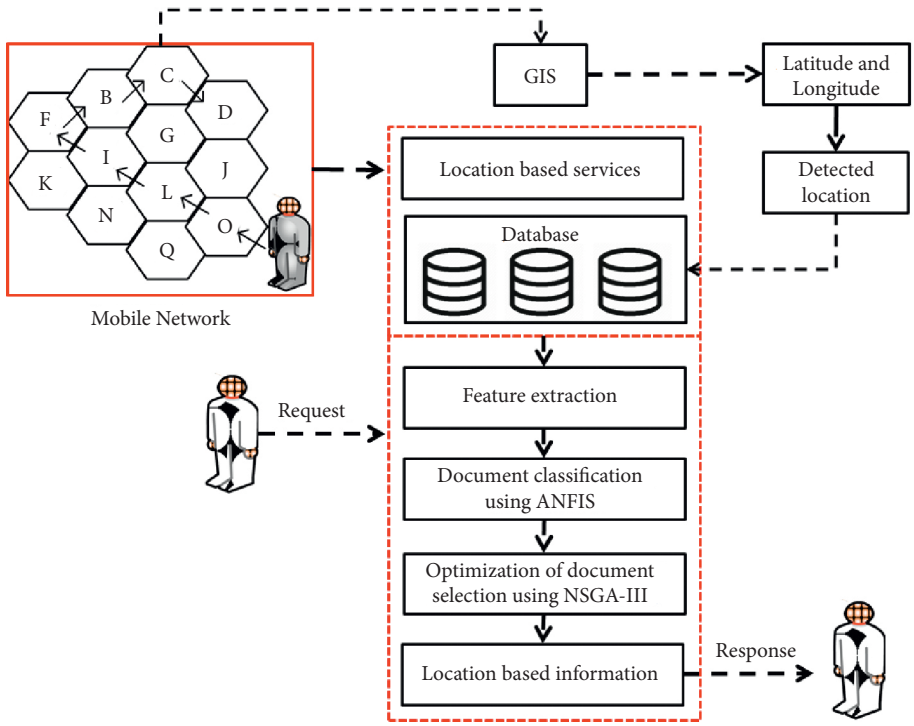

Figure 1: Proposed location-based advertising using ANFIS and NSGA-III.

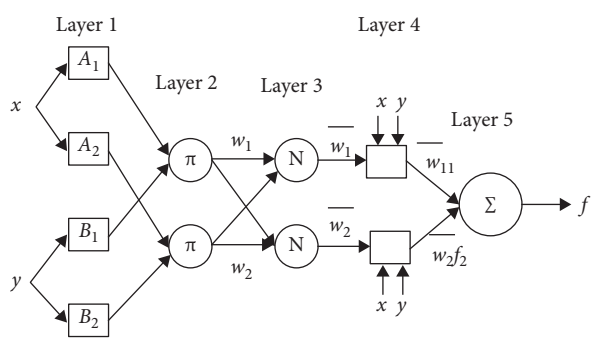

Figure 2: ANFIS-based classification model [36].

Initially, the features of LBS are assigned to the initial layer, i.e., fuzzy layer. It decomposes the feature values to fuzzy values. Every feature has its own fuzzy membership function [37]. A typical membership function can be defined as

$$f1 = \{(p_1 \cdot x + q_1 \cdot y + r_1), x == A_1,\ y == B_1\}, \quad (1)$$

where x and y are membership functions, A_1 and B_1 define membership values of x and y, $f1$ shows the fuzzy membership value, and p_1, q_1, and r_1 indicate fuzzy variables. Membership functions can be computed by considering the premise attributes a, b, and c.

Thereafter, rules layer is utilized. It evaluates the firing capabilities for the rules. Output of this node is shown using the product of all incoming edges.

The normalization layer is then used to normalize product values by evaluating sum of products and dividing every value on it. It can be computed as

$$W_{11} = \frac{W_1}{W_1 + W_2}, \qquad W_{22} = \frac{W_2}{W_1 + W_2}. \quad (2)$$

The defuzzification layer utilizes normalized values and consequence attributes p, q, and r, respectively. Output is the summation of inputs by using a constant. It can be evaluated as

$$\begin{aligned} O_i &= w_i f_i \\ &= w_i (p_i x + q_i y + r_i), \quad i = 1, 2. \end{aligned} \quad (3)$$

Finally, output layer evaluates the mean of every rule output. It can be computed as

$$W_i f_i = \frac{\sum_{i=1}^{i=n} W_i f_i}{\sum_{i=1}^{i=n} W_i}. \quad (4)$$

3.2. Nondominated Sorting Genetic Algorithm-III. NSGA-III [38] is extensively utilized to solve many optimization problems. It is an extension of genetic algorithm [39–41] and can solve optimization problems with many objectives. From the extensive review, NSGA-III is selected for optimization purpose. As it can handle multiobjective problems with better convergence speed, NSGA-III do not suffer from stuck in local optima and premature convergence issues too.

Table 1 shows nomenclature of NSGA-III. Initialization of population is shown in Algorithm 1. Random offsprings are evaluated and encoded to the initial LBS solution values.

Table 1: Definitions of NSGA-III's symbols.

Variable	Uses
η_i	Elite population
δ	Permutation vector
$\mathscr{G}$	Group of random offsprings
χ	Optimal offspring
a	Random number $\in\in[0,1]$
Θ	Group of δ', α''
α	Binary decision vector
ι	Encoding of random offsprings

$\delta' \leftarrow$ Optimal LBS.
$\delta'' \leftarrow \{\chi_1, \chi_r, \chi_{r-1}, \cdots, \chi_2\}$
$\alpha' \leftarrow$ Evaluate fitness of LBS.
$\alpha'' \leftarrow \phi \Theta \leftarrow \{\iota(\delta', \alpha''), \iota(\delta'', \alpha'')\}$
while
  $d' = \phi$ do
  $L \leftarrow$ Use LBS
  $M \in d'$ with better
  p_L / χ_L performance
  $\alpha'' \leftarrow \alpha'' \cup \{L\}$
  $\alpha' \leftarrow \alpha', \{L\}$
  if $(\delta', \alpha'')$is not dominated by (δ'', α'') then
    $\Theta \leftarrow \Theta \cup \{\iota(\delta', \alpha'')\}$
  else
    $\Theta \leftarrow \Theta \cup \{\iota(\delta'', \alpha'')\}$
  end if
end while
$\mathscr{A} \leftarrow$ obtain group of $a \times m$ offsprings from
Θ by considering random operator.
$\mathscr{M} \leftarrow$ compute group of $(1-a) \times m$ offsprings
$\eta^{(0)} \leftarrow \mathscr{M} \cup \mathscr{A}$
return $\eta^{(0)}$

Algorithm 1: Initial population.

Algorithm 2 represents the step-by-step flow of GANM: GIS, ANFIS, and NSGA-III-based LBS. Random offsprings are evaluated that represent the optimal solution of LBS. Thereafter, fitness of the developed LBS-based solution is computed.

Offsprings are then decomposed into nondominated and dominated sets. Mutation and crossover operators are then utilized to evaluate the fitness of each child offspring. Nondominated offsprings are then sorted using non-dominated sorting (). Final solution is returned when stopping condition met. $\iota(\delta, \alpha)$ converts random solutions (δ, α) as a solution of LBS.

Therefore, NSGA-III is used to select the optimal number of obtained-predicted LBS from the ANFIS model.

4. Performance Analysis

The performance of GANM is evaluated on MATLAB 2021a tool. The parameters of the NSGA-III are selected on trial-and-error basis. The used models for comparative analyses are also implemented using the same setup. The performance of GANM and the existing LBS models is compared by considering various performance metrics such as F-score, accuracy, sensitivity, specificity, and area under curve (AUC).

4.1. Comparative Analysis. Figure 3 shows the accuracy and loss analysis of GANM-based LBS. It is found that GANM achieves better accuracy and lesser loss values with respect to number of epochs. GANM achieves better convergence rate.

Figure 4 shows the F-score analysis among GANM and the existing artificial intelligence-based LBS models. It is found that GANM achieves efficient results with respect to number of user queries. GANM performs better than the existing models in terms of F-score by 2.2734%.

Figure 5 demonstrates the accuracy analysis among GANM and the existing artificial intelligence-based LBS models. It is found that GANM achieves efficient results with respect to number of user queries. GANM performs better than the existing models in terms of average accuracy by 2.3981%.

Figure 6 shows the F-score analysis among GANM and the existing artificial intelligence-based LBS models. It is

```
η̂_i ← randomly select 0.1m_i offsprings from η_i
for all T ∈ η̂_i do
    (χ, d) ← convert T as solution of LBS
    for M ← 1 to SE_χ do
        χ' ← compute a random offspring on LBS in χ
        if (χ', z) is not dominated by (χ, d) then
            (π, d) ← (χ', d)
        end if
    end for
    if (χ, d) is not dominated by any combination in η_i then
        η_i ← η_i ∪ {ι(χ, ν)}
    end if
    for t ← 1 to SE_d do
        i_t ← select an i_t ∈ {1, H} randomly.
        if i_t ∈ d then
            d' ← d, {i_t}
        else
            d' ← d ∪ {i_t}
        end if
        if (χ, d') not dominated to offspring in η_i then
            η_i ← η_i ∪ {ι(χ, d')}
        end if
    end for
end for
if |η_i| > m_i then
    η_i ← select m_i offsprings evaluated using NSGA-III
end if
```

Algorithm 2: NSGA-III-based optimal solution for LBS.

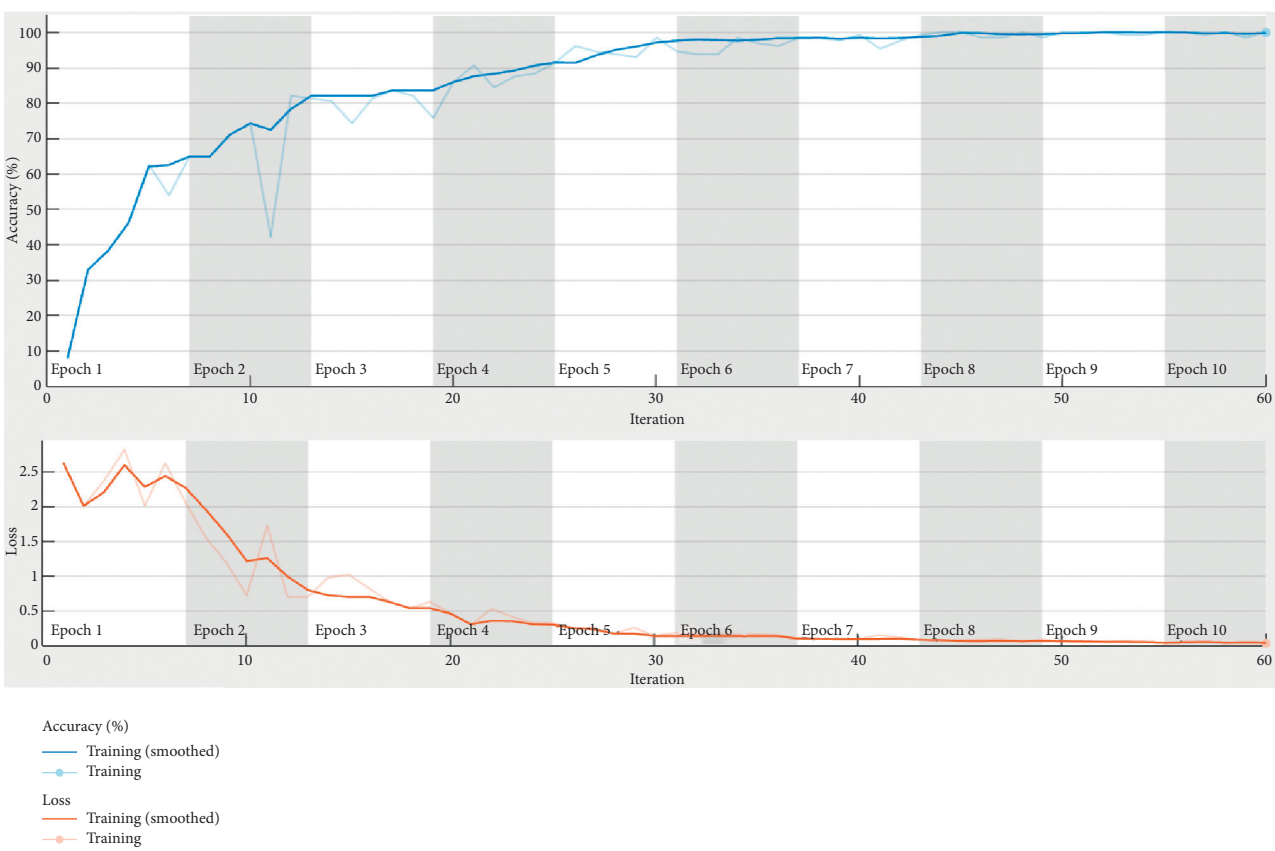

Figure 3: Sensitivity analysis of artificial intelligence-based LBS models.

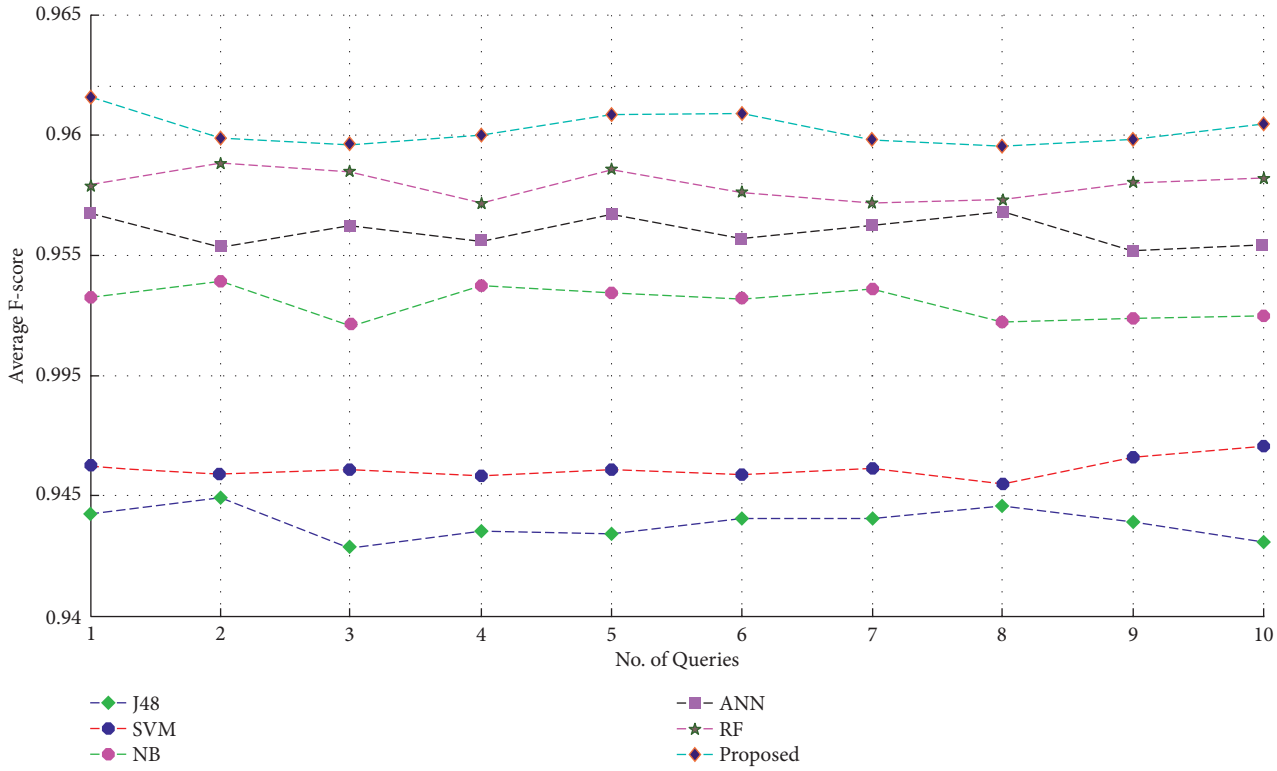

Figure 4: F-score analysis of artificial intelligence-based LBS models.

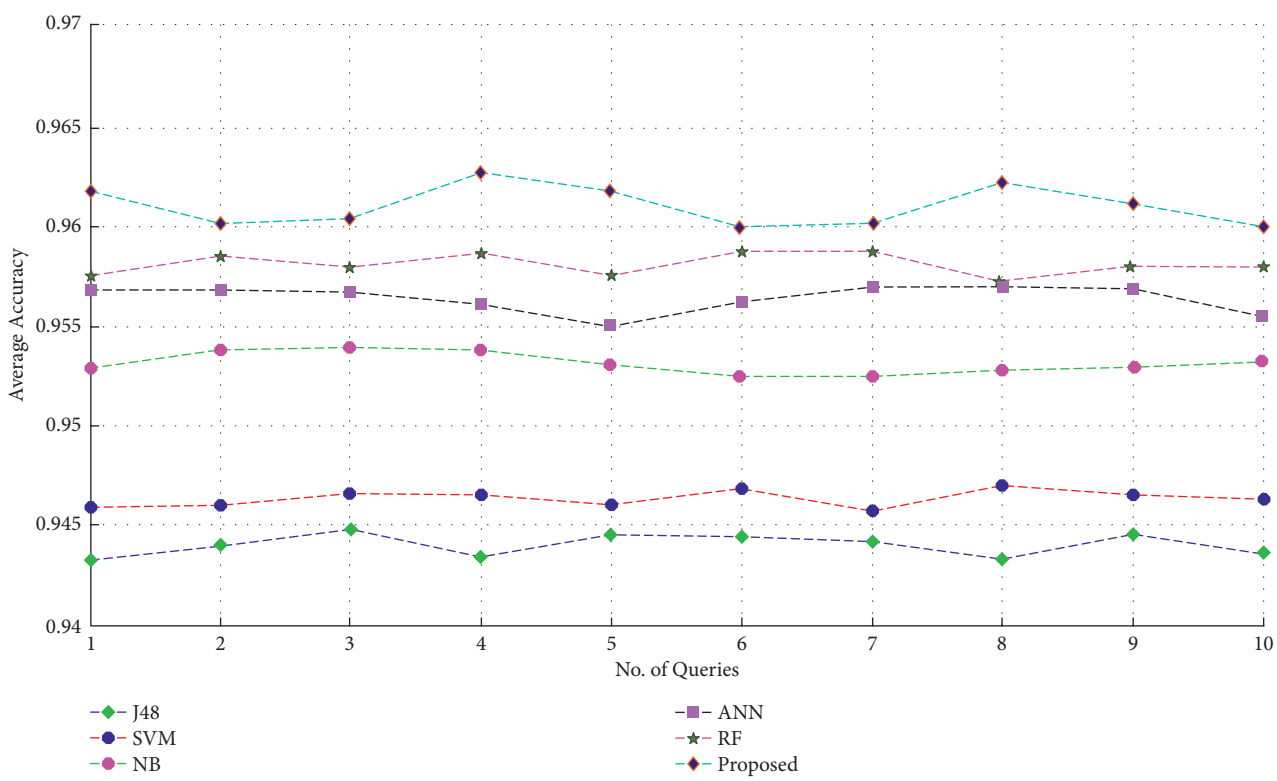

Figure 5: Accuracy analysis of artificial intelligence-based LBS models.

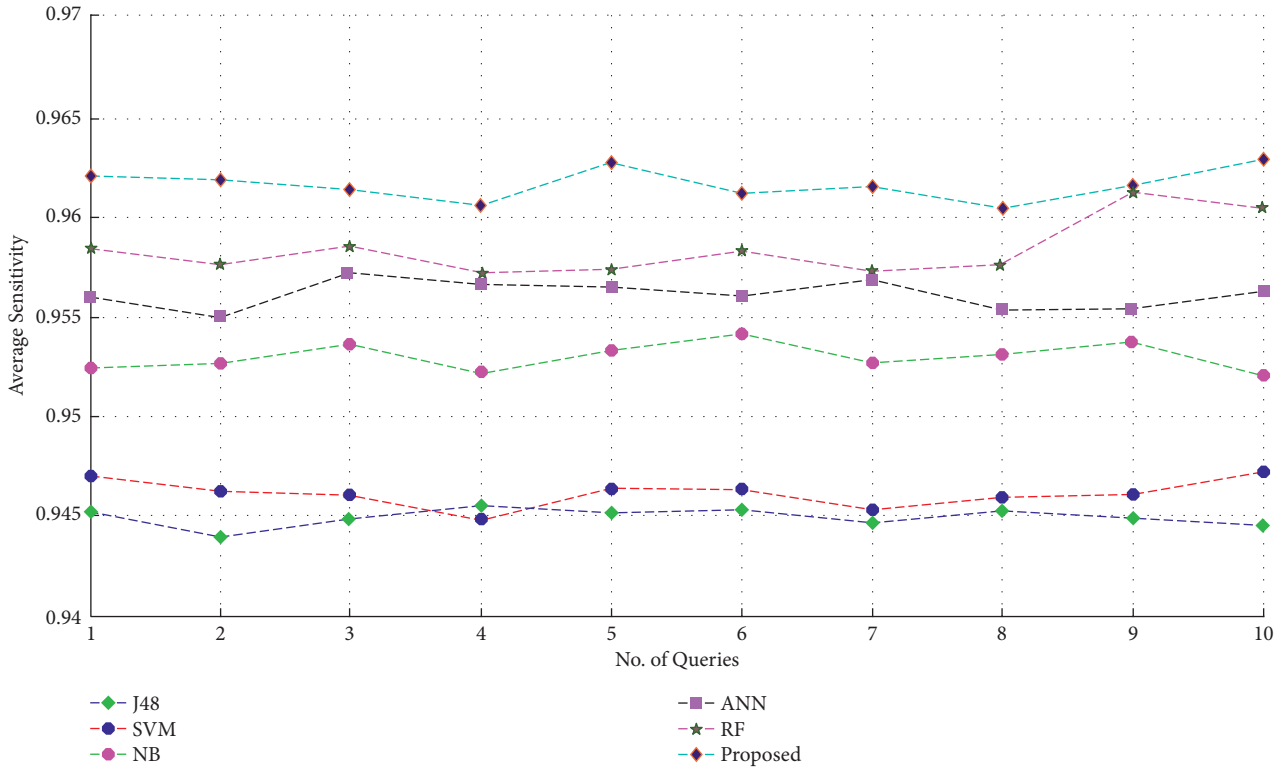

Figure 6: Sensitivity analysis of artificial intelligence-based LBS models.

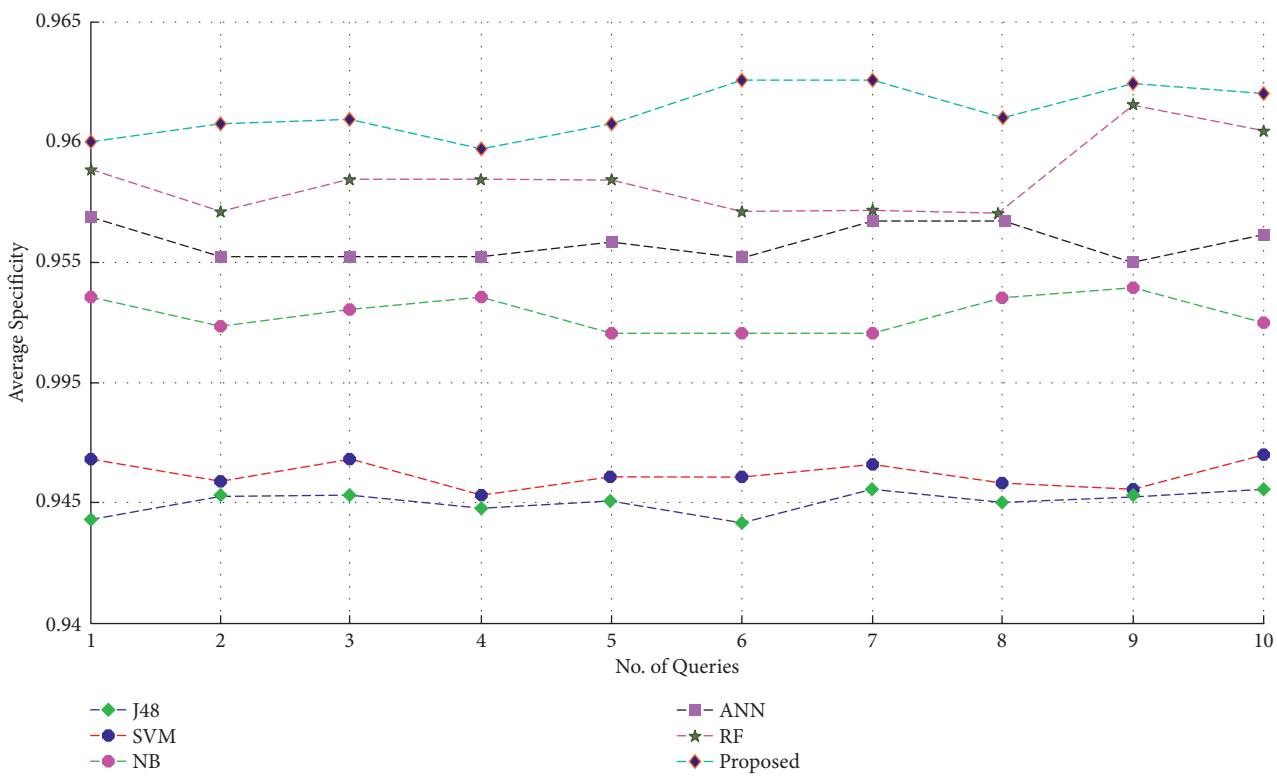

Figure 7: Specificity analysis of artificial intelligence-based LBS models.

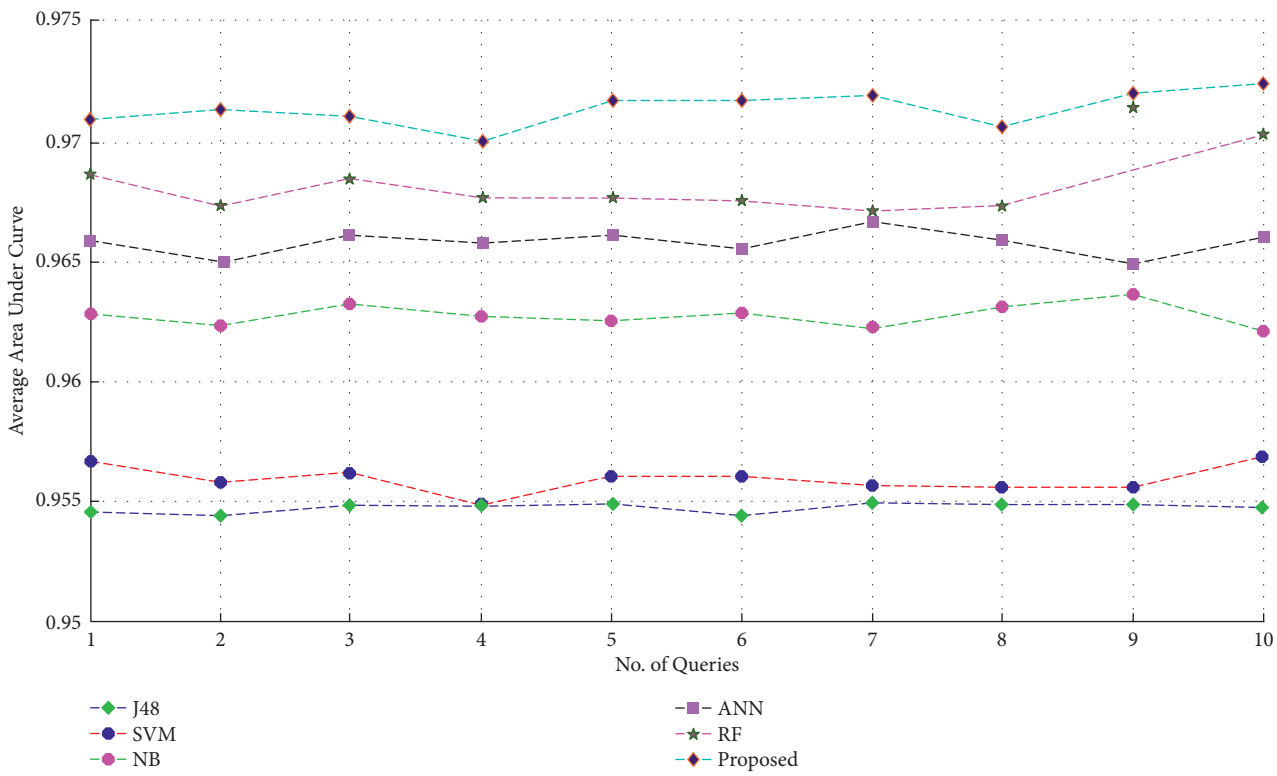

Figure 8: AUC analysis of artificial intelligence-based LBS models.

found that GANM achieves efficient results with respect to number of user queries. GANM performs better than the existing models in terms of sensitivity by 2.3947%.

Figure 7 demonstrates the accuracy analysis among GANM and the existing artificial intelligence-based LBS models. It is found that GANM achieves efficient results with respect to the number of user queries. GANM performs better than the existing models in terms of specificity by 2.4271%.

Figure 8 shows the F-score analysis among GANM and the existing artificial intelligence-based LBS models. It is found that GANM achieves efficient results with respect to the number of user queries. GANM performs better than the existing models in terms of AUC by 2.1638%.

4.2. Discussion. Extensive experimental results reveal that the proposed model achieves significantly better values than the competitive models. These competitive models are J48, SVM, NB, ANN, and RF. GANM outperforms the competitive models by achieving better convergence rate. It is observed that the proposed GANM outperforms the competitive models in terms of F-score, accuracy, sensitivity, specificity, and AUC by 2.2734%, 2.3981%, 2.3947%, 2.4271%, and 2.1638%, respectively.

5. Conclusion

An efficient machine learning and metaheuristic-based model was designed for LBS. Initially, the potential location information was evaluated utilizing GIS. Thereafter, significant features were computed using the location data. Obtained features were then segmented to improve the process of LBS. ANFIS was then utilized to efficiently classify the user data. Finally, the optimization of classified documents was achieved using NSGA-III. Extensive experiments were performed to validate GANM. Comparative analyses revealed that proposed GANM achieved better outcomes than the competitive models in terms of F-score, accuracy, sensitivity, specificity, and AUC by 2.2734%, 2.3981%, 2.3947%, 2.4271%, and 2.1638%, respectively.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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